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Currency Mismatch in the Banking Sector in Latin America and the Caribbean*

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Abstract: Existing literature uses data based on the residence principle to proxy for currency mismatch. This paper collects data on assets and liabilities broken by currency of denomination in the banking sector in Latin America and the Caribbean. I show that the information used in the literature cannot substitute for data broken down by currency and present new facts. I observe a reduction in long foreign currency positions, with several banking sectors taking short positions after 2006. Employing a methodology that accounts for time-varying unobservable characteristics, this reduction is shown to be partially explained by the implementation of prudential policies.

Keywords: currency mismatch, prudential regulation, foreign currency risk, dollarization, synthetic control method.

JEL Classification: G18, G21, F30

Resumen: En este documento, se levanta una encuesta entre diecisiete bancos centrales de América Latina y el Caribe, la cual permitió generar una nueva base de datos sobre activos y pasivos denominados en moneda extranjera para el sector bancario privado. Se muestra que los datos recogidos son más precisos para medir descalces cambiarios que aquellos que se recaban bajo los principios de residencia o de localización, por ejemplo, en las estadísticas del Banco de Pagos Internacionales o en las del Fondo Monetario Internacional. Asimismo, se muestra que la tendencia de las posiciones largas en moneda extranjera pasó de ser creciente a decreciente en la mayoría de países durante 2000-2012, con los sectores bancarios de muchas economías tomando posiciones cortas en moneda extranjera después de 2006. Utilizando una metodología que controla por características inobservables que varían en el tiempo, se muestra que este comportamiento en el índice de descalces cambiarios puede ser parcialmente explicado por la implementación de políticas prudenciales.

Palabras Clave: descalces cambiarios, regulación prudencial, riesgo cambiario, dolarización, método de controles sintéticos.

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1. Introduction

The latest crisis reminded of the importance of foreign currency risk for financial stability (see Terrier et al., 2011).¹ Foreign currency risk represents a major threat for highly dollarized economies such as some countries in Latin America and the Caribbean. However, insufficient data collection currently exists to properly measure currency mismatches in these economies. The contribution of this paper is twofold. First, I conduct a survey across central banks and construct a unique dataset to measure currency mismatches in the banking sector. Second, I use this unique dataset to evaluate prudential policies employing the synthetic control method (Abadie and Gardeazabal, 2003 and Abadie et al., 2010) which, to the best of my knowledge, has never been used to this end.

The contemporary economic history of some Latin America and Caribbean countries is characterized by periods of high inflation and currency crises. In some nations, these crises reduced confidence in the local currency and led to a process of partial dollarization (Alvarez-Plata and García-Herrero, 2007).² Since partial dollarization is frequently associated with currency mismatches, it may generate financial risk: When the exchange rate adjusts, currency mismatches create balance sheet problems that may propagate throughout the economy. Furthermore, the banking sector may play a significant role in propagating this financial risk (see, for instance, Krugman, 1999; Corsetti et al., 1999, Cespedes et al., 2000, Aghion et al., 2001 and Allen, 2002). Hence, measuring currency mismatches in the banking sector is of the first order of magnitude for some economies in Latin American and Caribbean.

An extensive literature has addressed the necessity of measuring currency mismatch and constructed different classes of indicators (Bussiere and Mulder 1999; Eichengreen and Hausmann, 1999 and 2003; Eichengreen et al.; 2002; Eichengreen, Hausmann and Panizza, 2003; Goldstein and Turner, 2004 and Lane and Shambaugh, 2010a and 2010b).³ The original sin indicators have been criticized for ignoring the asset side of the balance sheet,

¹ Terrier et al. (2011) highlight the relevance of currency mismatches for Eastern European banks.

² In some countries, residents substituted domestic currency-denominated assets and liabilities with U.S. dollar-denominated wealth. The banking sector in some Latin America and Caribbean economies still is among the most financially dollarized banking sectors in the world (Alvarez-Plata and García-Herrero, 2007). ³ Section 2 explains why Lane and Shambaugh 2010a and 2010b are considered in this literature.

i.e. FX assets used for hedging currency risk. The external vulnerability indicators use data based on the residence principle that are not broken down by currency of denomination, i.e. balance of payment data, for instance, are broken down by the residence of assets and liabilities' holders. Moreover, these data are collected at the country-level and are thus unable to identify mismatches in the domestic market. Therefore, using country-level data based on the residence principle is even more inappropriate when residents establish foreign currency relations on a regular basis (in highly dollarized economies such as some of the Latin American and Caribbean countries).

In order to circumvent these issues, I collect data on FX assets and FX liabilities in the private banking sector of highly dollarized economies. The data refer to both sides of the balance sheet; they are broken down by currency of denomination and they are collected at the sectoral-level.⁴ Furthermore, the information is comparable at the highest possible level across seventeen Latin American and Caribbean economies because the collection process is based on accounting manuals for banking institutions.

The paper shows that data based on the residence and data broken down by currency of denomination are different. In Section 3, I construct a currency mismatch indicator based on my dataset and proxies for this indicator with data based on the residence and the locational principles (Bank for International Settlement's locational statistics, BIS, and the Banking Survey of the IMF's International Financial Statistics). I calculate correlation coefficients between my indicator and the proxies by country. For the proxy based on BIS data, the cross-country average of the correlation coefficients is 0.185 and the coefficient is above 0.7 only for Jamaica and Guatemala. When the proxy is based on data from the Banking Survey of the IMF, the average coefficient is 0.191 and Jamaica and Brazil are the only economies with a coefficient above 0.7. These outcomes indicate that, when measuring currency mismatches in Latin America and the Caribbean, the residence principle is not a good proxy for a currency breakdown.

⁴ The currency mismatch indicators relate to the works of Arteta (2005), Pratt (2007) and Ranciere et al. (2010). However, my indicators consider all components of the balance sheet; they refer to highly dollarized economies and are used for policy analysis (see Section 1 for a thorough comparison).

Having established that my dataset represents an improvement, I formally present two indicators that capture different dimensions of currency mismatch. The first indicator measures the average level of currency mismatch and the second indicator, mentioned in the previous paragraph, indicates whether foreign currency positions are on average long or short. The behavior of these indicators across countries and over time reveals novel stylized facts. First, banking sectors with a higher level of currency mismatch were more exposed to foreign currency risk over 2000-2012 for two reasons: (a) Their mismatches were greater on average in the sense that the mean of the ratio of FX assets-to-FX liabilities was higher in these economies and (b) Their currency mismatches were more extreme given that this ratio also took the largest values in these countries. Second, there was a reduction in long foreign currency positions in most banking sectors of the Latin America and the Caribbean considered in the sample. Third, the trend of the ratio of FX assets to FX liabilities went from increasing to decreasing and short positions were taken in several banking sectors, mostly after 2006.

The currency mismatch indicators and the synthetic control method are used to evaluate prudential policies (Abadie and Gardeazabal, 2003 and Abadie et al., 2010). The synthetic method controls for unobservable characteristics that vary over time and, therefore, circumvents issues with the standard difference-in-difference techniques (see Section 6 for the relevance of unobservable characteristics in evaluating prudential policies). I focus on a policy that is relevant for highly dollarized economies: Reductions in the limit on long foreign currency positions and increases in the limit on short positions. I find that these policies reduced long positions and the average level of currency mismatch in Bolivia, Paraguay and Peru. On average over five post-intervention quarters, the policies reduced the ratio of FX assets to FX liabilities between 1.78 and 2.66 percent, depending on which countries are considered in the mean (see Section 6 for details).

This paper is closely related to an emerging literature that studies the effects of FX macroprudential policies on different risk dimensions. Dell'Ariccia et. al. (2012) find that macroprudential tools reduced the probability of credit booms in 22 Central and Eastern European countries over 1985-2009. Ostry et al. (2012) show that tighter FX prudential measures are associated with reductions in domestic foreign currency borrowing and the

use of debt in the banking system. Lim et. al. (2011) show that limits on foreign lending reduce the pro-cyclicality of leverage, and that limits on net open foreign positions reduce external indebtedness. However, none of these papers study the effects on currency mismatch, measured with data broken down by currency of denomination on all components of the balance sheet. Their treatments are not defined as changes in limits on foreign currency positions and neither of the papers uses the synthetic control method.

Finally, some points deserve to be made. The currency mismatch indicators that I construct measure the exposure to foreign currency risk that can be inferred from banks' balance sheets. I do not claim in this paper that this is all foreign currency risk that banks face. The banking sector can face risk associated with lending to unhedged borrowers (FX credit risk in terms of (Terrier et al., 2011) or with financial instruments that do not appear in the balance sheet (see Tobal (In press) for a role of financial derivatives in Latin American and the Caribbean and Section 3 for a discussion on the relevance of financial derivatives for some Latin American and Caribbean economies). Nevertheless, I believe that both the dataset and the indicators that I construct represent an improvement over the existing literature and contribute to understand how currency mismatches behave. Furthermore, given that most FX policies in the region apply to the banking sector, the data on banks' balance sheets allows me to perform policy analysis.

The paper is structured as follows. Section 2 reviews the literature on currency mismatch indicators at the country and at the sectoral levels. Section 3 explains the main features of the collection process. Section 4 addresses issues with the data and compares my indicators with proxies that use data based on the residence principle. Section 5 analyses the behavior of the indicators across countries and over time and Section 6 performs the policy analysis. Section 7 concludes.

2. Currency Mismatch Indicators: Aggregate and Sectoral Levels

The financial crises of the 1990s have triggered a large literature on currency mismatch indicators at the aggregate level. The earliest works have linked currency mismatch to original sin, a country's inability to borrow abroad in its own currency (Eichengreen and Hausmann 1999 and 2003; Eichengreen et al., 2002 and Eichengreen, Hausmann and

Panizza, 2003).⁵ Thus, the greater the proportion of foreign currency-denominated securities, the greater original sin is, and therefore the greater a country's mismatches are. However, the use of original sin indicators as a proxy for currency mismatch has been criticized for considering a single side of the balance sheet; assets and liabilities can be both used to hedge FX positions (Goldstein and Turner, 2004).

The external vulnerability indicators are also constructed at the aggregate level; they consider both sides of the balance sheet and have proved powerful for predicting financial crises (Goldstein and Turner, 2004). Nevertheless, they use data based on the residence principle that are frequently not broken down by currency. These data identify a country's imbalances vis-á-vis non-residents but are silent on their currency of denomination (Brussiere and Mulder, 1999 and Goldstein and Turner, 2004).

Lane and Shambaugh's (2010a) aggregate indicator of currency risk circumvent the issues of the original sin and the external vulnerability indicators by accounting for the currency composition of both sides of the international balance sheet.^{6,7}Although their goal is not to proxy for currency mismatch, their seminal measure could in principle be used to this end. A problem with this approach is the use of country-level data: In the aggregation process, currency mismatches among residents cancel out. Therefore, country-level data ignore mismatches in the domestic market and cannot identify FX risk at the sectoral-level (Goldstein and Turner, 2004 and Ranciere et al., 2010).⁸

A recent literature has pointed out that currency mismatch indicators should use data dissagregated at sectoral-level and account for mismatches in the domestic market. Allen et al. (2002) argue that foreign currency debt among residents may create domestic mismatches. Reinhart et al. (2003) highlight the lack of reliable data to calculate linkages at the sectoral-level, indicating that data unavailability still hinders progress in the literature.

⁵ Thus, there may be mismatches because investments generate revenues denominated in domestic currency.

⁶ Lane and Shambaugh (2010a) quantify the valuation channel, the impact of capital gains and losses.

⁷ Along the same lines, Lane and Shambaugh (2010b) provide stylized facts on the cross-country and timeseries variation in aggregate foreign currency exposure embedded in international balance sheets.

⁸ Overlooking domestic mismatches is not the result of their being aggregate indicators, but rather the result of their being based solely on country-level data. For instance, Goldstein and Turner (2004)'s aggregate measure of currency mismatch employs data on domestic assets and liabilities and therefore, captures domestic currency mismatches partially.

In Section 4, I construct measures of currency mismatch that incorporate the improvements of the literature on aggregate level indicators and, importantly, use data disaggregated at the sectoral level. The measures of currency mismatch that I construct consider both sides of the balance sheet (as the external vulnerability indicators do); my indicators are based on data broken down by currency (following Lane and Shambaugh) and are constructed for the banking sector in the manner of the recent literature.

The recent literature has investigated currency mismatch in the banking sector. Employing annual data on foreign currency deposits and loans for 37 countries, Arteta (2005) shows that currency mismatches are greater under exchange rate flexibility. In contrast with my work, his paper uses data only credit and loans; it employs data up to 2000 and does not focus on prudential policies. Pratt (2007) finds that currency mismatches play a significant role for the determination of emerging sovereign bond spreads. She constructs currency mismatch indicators for the banking sector in 25 emerging countries. However, her sample does not include most of the countries with a high degree of financial dollarization considered in my sample (see Goldstein and Turner, 2004);⁹ along the same lines, she does not investigate the relevance of using data broken down by currency vis-á-vis data based on the residence principle; she uses data up to 2005; she does not study the behavior of currency mismatch across countries and over time and does not evaluate the effect of policy interventions.

Finally, Ranciére et al. (2010) construct a measure of currency mismatch that controls for bank lending to unhedged borrowers to capture systemic risk. They construct the measure for 10 emerging European economies for which the data is readily available. In an extension, they repeat the exercise for other 19 emerging countries, but they are forced to use data based on the residence principle for most Latin American economies considered in their sample. In their own words, the data collection effort in Eastern Europe "seems unparalleled in the rest of the emerging world, despite the role of currency mismatch in the financial crises of the 1990s." By collecting data on foreign currency assets and liabilities for the banking sector in Latin America and the Caribbean, my paper fills this gap.

⁹ Goldstein and Turner (2004) show Argentina and Peru are the countries with the highest share foreign currency of total debt. Both are Latin-American countries with high levels of dollarization over the period.

3. Collecting Data and Making it Comparable

3.1 Data Collection Process

The data collection process comprised two stages. In the first stage, I sent a survey to the heads of the research and financial stability departments of the central banks; then, within each central bank, the survey was distributed to the personnel who were best qualified to answer the questions. The second stage comprised a series of contacts made by email or by phone and personal interactions that I maintained with officials from several central banks. The second stage enabled me to complement the information provided in the first delivery of the survey.

The two stages were employed to ensure the highest possible level of comparability across countries. In particular, two requirements were fulfilled: the data provided by each central bank referred to a similar set of financial agents and to a similar set of assets and liabilities. The following strategy helped me define the set of financial agents: I inquired data on the "Banking Sector" in the first stage of the process, and redefined the set upon which the data would be requested in the second stage. The set of financial agents was defined as "Commercial Banks," since most surveyed countries were able to provide data for these agents. The remaining central banks provided information for at least a "similar but slightly more aggregated" set and were asked which proportion they though commercial banks represented in this set. As shown below, commercial banks represent a substantial portion of most financial systems; the data referred to a highly representative set of agents.

I also ensured that the information referred to a similar set of assets and liabilities. To this purpose, I guided the central banks about the process of data delivery by providing them with categories of foreign currency assets and liabilities. The categories would force central banks to provide data on similar assets and liabilities and, importantly, not to leave aside any relevant information. I contacted officials from the Banco de la Republica, Colombia, to help me create the categories based on their accounting manual for financial institutions: They formed five categories and created a link between each foreign currency account from their manual to one of them. I then used this link a benchmark: I linked the accounts of

each country to a foreign currency account from Colombia's accounting manual and, therefore, to one of the five categories created by the Banco de la Republica.^{10,11}

In the second stage of the collection process, central banks received the account-category allocation for their country and the original allocation provided by the Banco Central de la Republica. When delivering the data, they were free to use the allocation that I had created or to use Colombia's allocation to create their own. It was emphasized that they should deliver data on all the foreign currency assets and liabilities that appeared in Colombia's allocation. The fact that central banks knew Colombia's example and had freedom to apply it to their own country precluded misinterpretations and ensured the data was comparable.

3.2. The Data Collected

Seventeen central banks delivered the requested data. Table 1 lists the countries and the available spam of time. The period of interest was defined as 1992Q2-2012Q2; all central banks were asked to provide information on every quarter for which data were available. The availability varies across countries: whereas Chile; Paraguay and the Eastern Caribbean Countries provided data on more than 70 quarters, Nicaragua delivered information on 39. With the exception of Brazil; Peru and Nicaragua, whose samples commence in 2001 (Brazil and Peru) and in 2003 (Nicaragua), all countries delivered data beginning in 2000 or earlier. Every central bank provided quarterly data as requested.

Regarding the set of financial agents, Table 2 depicts the proportion that commercial banks represent in the data delivered (according to the officials from the central banks). The information cannot be separated into data on commercial banks and data from other financial institutions only in Argentina, Jamaica and Paraguay. Commercial banks represent over 95% of the data in the former two countries and 75% in Jamaica, whose sample also includes data on two additional types of deposit-taking institutions: building societies and FIA Licensees.

¹⁰ I thank Mrs. Luisa Silva Escobar (Banco de la República, Colombia) for her invaluable assistance.

¹¹ For the non-Spanish speaking countries, I employed Monaco's accounting manual as a benchmark because its structure is similar to that proposed by the Banco de la Republica, Colombia.

4. The Residence Principle and Derivatives

4.1 The Residence Principle

To show that data based on the residence principle and data broken down by currency generate different results, I compare two indicators of currency mismatch. I construct the ratio of FX assets to FX liabilities employing my dataset and compare this indicator with proxies that use data based on the residence principle. I call these proxies "most similar indicators" and construct them with data from the Bank for International Settlements's locational statistics (BIS) and from the Banking Survey of the IMF's International Financial Statistics.

First, I compare my dataset to the BIS's locational statistics.¹² These statistics provide information on aggregated international claims and liabilities for all banks resident in the reporting countries. The data are broken down by counterparty so that I can retrieve the information for the Latin American and the Caribbean economies vis-á-vis these reporting countries. The "most similar indicator" is then calculated as the ratio of international claims to international liabilities.

Table 3 displays the correlation coefficient between my measure and its most similar BIS indicator for the 15 countries with available data in the locational statistics over the period 2000/Q1-2012/Q3.¹³ The correlation between the indicator and its proxy is generally low; the cross-country average of the coefficients is 0.185. Moreover, the coefficient is above 0.7 only for Jamaica and Guatemala, two countries with moderate-low levels of financial dollarization. On the other hand, the coefficient is below 0.7 for Bolivia, Costa Rica, Honduras, Nicaragua, Paraguay, Peru and Uruguay, which are the economies with the highest level of financial dollarization (see Galindo and Leiderman, 2005, Leiderman et al. 2006, Cayazzo, et al., 2006, Rennhack and Nozaki, 2006, Sánchez, 2006, Sherene, 2007, Leon and Reveiz, 2008, and Bachay et al., 2009 for a review on financial dollarization in

¹² Commercial banks represent a significant proportion of the financial system in most economies and, therefore, the difference between the set of banks considered in each dataset should not be large.

¹³ When data for a specific quarter was not available, this quarter was excluded from the sample.

the region). These outcomes indicate that data broken down by currency and data based on the locational principle lead to different outcomes.

Table 4 depicts the correlation coefficients between my currency mismatch indicator and a proxy that uses data from the Banking Survey of the IMF's International Financial Statistics (IFS). The most similar indicator is defined as the ratio of foreign assets to foreign liabilities. Note again that coefficients are in general low: the cross-country average coefficient is 0.191 and Jamaica and Brazil are the only economies with a coefficient above 0.7. This evidence reveals that data broken down by currency cannot be substituted with data based on the residence principle.

4.2 Derivatives

None of the currency mismatch indicators or data sources that have been mentioned in this paper contains information on financial derivatives. However, it has been argued that an appropriate measure of currency mismatch should account for this information. The argument is that banks could use these financial instruments to hedge foreign currency positions (Goldstein and Turner, 2004). However, data on derivatives are frequently not available since, in most cases, they do not appear on balance sheets. Regarding several Latin America and the Caribbean countries, derivatives are off-balance sheet in most of them so that many central banks were unable to deliver the data. Moreover, even in some of the countries where this information appears in the balance sheet, the accounting manual does not distinguish between derivatives that are used to hedge FX risk and other derivatives.

Although conceptually it is relevant to include data on derivatives, in practice, not counting with this information is less critical: The degree of development in the derivatives markets of some Latin America and Caribbean is low. I construct a proxy for this degree of development with the intention of supporting my argument. The proxy is defined as the ratio of the sum of derivatives assets and liabilities to the sum of total assets and liabilities, regardless of currency of denomination. Table 5 displays this proxy for the three countries that delivered data on derivatives. Chile provided monthly data from January of 2010 to

July of 2013; the information available for Nicaragua is from January of 2008 to June of 2006 and the Banco de la Republica, Colombia, delivered quarterly data from 2000 to 2012. Note that the ratio equals 0.0007 and 0.037 for Nicaragua and Chile, respectively, indicating moderate degrees of their derivatives markets. The ratio is 0.1217 for Colombia, where the financial derivative market is more developed than in the other two countries.

5. Currency Mismatch Indicators

This section presents two indicators that capture different dimensions of currency mismatch in the banking sector. The first indicator is written as follows

$$CMABS(iT) = \left[\sum_{t=0}^{t=T} |CM(it) - 1|\right] / T$$

$$CM(it) = FXAssets(it) / FXLiabilities(it)$$
(1)

where FXAssets(it) and FXLiabilities(it) are foreign currency assets and liabilities held by the banking sector in country *i* at quarter *t*, respectively, CM(it) is the ratio between these assets and liabilities, $|\cdot|$ denotes absolute value, the first quarter has been normalized to 0 and CMABS(iT) is the mean of |CM(it)-1| over time. The consideration of absolute values makes CMABS(iT) silent on whether there is a short or a long foreign currency position. On the other hand, it ensures that these positions do not cancel each other out, and therefore that CMABS(iT) reflects the average level of currency mismatch.

Table 6 and Figure 1 display the mean and the standard deviation of |CM(it)-1| over 2000-2012 for the 17 countries.¹⁴ The cross-country correlation between the mean and the standard deviation is positive and strong (the correlation coefficient is 0.925 for the 17 countries). Thus, the countries with higher CMABS(iT) were more exposed to foreign currency risk for two reasons: (a) Their mismatches were greater on average and (b) Their currency mismatches were more extreme.

¹⁴ Twelve countries have data available for 2000 and 4 of the remaining economies have data available a year later; therefore, I start the sample in 2000. For the remaining countries, the period considered begins in the first available quarter. For all countries, the period ends in the last available quarter.

The second indicator is written as follows for a country *i* over a T quarters period

$$CM(iT) = \sum_{t=0}^{t=T} CM(it) / T$$
(2)

where CM(iT) is the mean of CM(it) over time. This second indicator reflects whether the average foreign currency position taken by banks is long or short. CM(iT) > 1 indicates the average position is long and CM(iT) < 1 indicates that positions are on average short.

Table 7 and Figure 2 display rates of change in CM(iT) by country over time. The rate of change is calculated as the log difference between an initial mean (the average of CM(it) over 2001Q2-2002Q1) and a final mean (the average of CM(it) over 2011Q3-2012Q2).¹⁵ For 12 out the 16 economies considered in Table 7, the rate of change is negative: There was a reduction in long positions in most banking sectors of Latin America and the Caribbean.¹⁶

Furthermore, nine of these banking sectors took short foreign currency positions over 2000-2012. For these countries, short and long positions partially cancel each other out and, therefore, CM(iT) < CMABS(iT) + 1. Tables 6 and 8 show this inequality holds for Bolivia, Uruguay, Paraguay, Peru, Brazil, Chile, Colombia, Dominican Republic and the Eastern Caribbean Countries. I represent the time behavior of CM(it) and its trend in Figures 3-10 for these economies (the Hodrick–Prescott filter is used for the trends).

Note in Figures 3-10 that most short foreign currency positions were taken over 2007-2012. From 2008 on, all CM(it) trends decreased monotonically (a few months in Chile and Paraguay are the exception). Between 2005 and 2008, there was a break in most countries: The trends went from increasing to decreasing, and reached its minimum over the period 2002-2012 in either 2011 or 2012 for 8 out of the 9 economies (and also in Uruguay as the 2002 crisis is not considered). Putting all this together, the reduction in long

¹⁵The rate of change is calculated between means to avoid that a single observation drives the results. The periods 2001Q2-2002Q1 and 2011Q3-2012Q2 are chosen to calculate the means because all countries, with the single exception of Nicaragua, have data available for these periods of time.

¹⁶ In Table 6, the cross country initial mean is 1.18 and the average of the final mean is 1.03. Figure 3 excludes Chile and Jamaica so as not to distort the scale of the graph

positions and the emergence of short positions are a relatively recent phenomenon: That is, they did not become common until the late 2000's.

Bolivia, Uruguay, Paraguay and Peru, four of the economies with short positions, have similar patterns. First, they are the economies with the four lowest CMABS(iT) and four of the five lowest CM(iT) (the smallest currency mismatches and the shortest positions on average). Second, the reduction in their long position was great, even after controlling for initial CM(iT) means (Figure 2 shows the rate of reduction is increasing in the initial mean; the four countries appear below the regression line in this figure).¹⁷ Third, their central banks and financial supervisors implemented de-dollarization policies to reduce their relatively high levels of financial dollarization. Hence, it is natural to think that these de-dollarization policies partially explain the low values of CMABS(iT) and CM(iT) and the great reduction in long positions. The next section shows that some of the prudential policies taken by Bolivia, Paraguay and Peru did reduce CM(iT) and CMABS(iT).

6. Empirical Analysis

6.1. Policies Studied

This section evaluates the effectiveness of prudential policies in reducing currency mismatches in three highly dollarized economies: Bolivia, Paraguay and Peru. The analysis focuses on limits on foreign currency positions (limits, hereafter). Specifically, the treatment is defined as a decrease in the limit on long positions (e.g. from 70 percent to 50 percent of banks's capital) and/or as an increase in the limit on short positions. I study whether these policies reduced CM(it) (the outcome variable) over 2000-2012 and infer from the results whether they reduced the average currency mismatch, measured by the mean of |CM(it)-1|.

6.2. *Methodology*

¹⁷ The correlation coefficient between the rate of change and the initial equals is -0.824 for 16 countries considered in Table 6.

The effect of a policy is the difference between the post-intervention outcome and the counterfactual, i.e., the outcome that would have been observed in the absence of the intervention. When estimating policy effects, however, comparative case studies replace the counterfactual with the outcome trajectory of a control group. Yet, this trajectory does not replicate the counterfactual properly in the presence of time-varying unobservable characteristics: In the presence of these characteristics, the outcome trajectory of the treated country and that of the control group differ, regardless of the intervention.

Prudential policies are associated with unobservable characteristics that vary over time. Take the case of a country that implements a limit to reduce currency mismatch growth ("the treated country"). The fast growth is likely to be driven by these characteristics and, therefore, the outcome trajectories would have been different in the absence of the intervention. This fact poses a problem for difference-in-difference techniques because they cannot control for time-varying unobservable characteristics, and consequently yield biased estimates of policy effects. The use of difference-in-difference techniques has raised concerns about potential misestimates in the recent literature on FX regulation but also in the literature on capital account liberalization (see, for instance, Tamirisa, 1999; Bonfiglioli, 2005; Dell Ariccia et al. 2012; Lim et al. 2001 and Ostry et al. 2012).¹⁸

The synthetic control method (Abadie and Gardeazabal, 2003 and Abadie et al., 2010) overcomes this flaw; it controls for unobservable characteristics that vary over time by constructing a synthetic unit and using this unit as the counterfactual. The outcome trajectory of the synthetic unit results from assigning a weight w_j to the trajectory of each country within the control group. Importantly, the weights are chosen so that the synthetic unit most closely resembles the treated country in the pre-intervention period: The vector of weights W is chosen so as to minimize $(X_1 - X_0W)'V(X_1 - X_0W)$, where X_1 and X_0 contain pre-intervention values of predictors of the outcome variable for the treated and for the control countries, respectively, and V is a diagonal matrix that reflects their relative

¹⁸ Qureshi et al. (2011) and Ostry et al. (2011) relate endogeneity and reverse causality to the lack of association between capital controls and capital inflows. Along the same lines, Kraay (1998) argues that endogeneity explains the ambiguity of the empirical evidence on the impact of capital account liberalization. See Tamirisa (1999), Bonfiglioli (2005), Dell Ariccia et al. (2012) for other articles that relate endogeneity to identification in the context of prudential regulation.

importance (See the Appendix Section for a mathematical approach to the synthetic method in my dataset). Hence, when constructing the synthetic unit, the synthetic control method accounts for differences in outcome trajectories over the pre-intervention period and, therefore, for unobservable characteristics that vary over time.

6.3 Application to the Dataset

The analysis is carried out over a period of eleven quarters centered at the intervention period. This period is normalized at t=0 so that the event window is written as $t \in [-5,5]$.¹⁹ In the manner of Abadie and Gardeazabal (2003), the outcome variable (CM(it)) is included in the matrices X_1 and X_0 ; the predictors' matrices then consider three variables: CM(it), the rate of change in the exchange rate and the exchange rate itself, normalized by its mean value over the event window.²⁰ Since all outcomes are the same, regardless of whether the latter two predictors are included, I only consider CM(it).^{21, 22} For each policy, the control group is defined as the set of countries that neither reduced the limit on long positions nor increased the limit on short positions during the event window.²³

In order to evaluate a policy, I study the difference between the outcome trajectory of the treated country and that of the synthetic unit after the intervention. However, this difference might be driven by events other than the policy that occurr either at the intervention quarter or during the post-intervention period (the synthetic method accounts for events or policies that occur before the intervention).²⁴ I follow three strategies tackle this issue. First, I

¹⁹ Choosing a shorter event window would have left me with fewer pre-intervention periods to calculate the synthetic weights. Choosing a longer window would have reduced the number of policies available for study. ²⁰ The normalization of the exchange rate ensures the values are comparable across countries.

 $^{^{21}}$ See Appendix B in Abadie and Gardeabazal (2003) for a theoretical treatment on the case where the outcome variable is the only predictor.

²² The V matrix is given by the default option in Stata. This option chooses V using a regression that finds the best fitting W conditional on this regression.

²³ The synthetic method takes into consideration permanent differences in CM(it) originated before the event window because weights are chosen based on similarities with the treated country. Temporary effects of these policies, however, may alter the time behavior of CM(it) only for a few periods and, therefore, contaminate the choice of the synthetic weights. To tackle this issue, I define the control group as those countries that did not implement the policy during the entire event window,

²⁴ See note 21 for differences in CM(it) originated during the pre-intervention period or before.

construct average trajectories by taking the mean of CM(it) across: (i) treated countries and (ii) their synthetic units, and study the difference between these trajectories. The difference between these average trajectories should be less affected by specific events because the means are taken over policies implemented by different countries and at different moments of time Second, I calculate the averages with and without considering Peru; this strategy is relevant because Peru took several policies of the same type within the same event window. Third, only countries that neither increased the limit on long positions nor reduced the limit on short positions during the event window are considered.²⁵

6.4 Case Studies: Results

Three countries implemented policies fulfilling the conditions mentioned in the previous subsection over 2000-2012: Bolivia, Peru and Paraguay.²⁶ This is not surprising given that, as mentioned in Section 5, their levels of financial dollarization are among the highest in the region. Furthermore, the three countries were among the economies with the lowest CMABS(iT) and CM(iT) and with the greatest reduction in long positions, conditional on initial means. I proceed by studying three policies implemented in these countries.

The limit on long foreign currency positions for banks in Bolivia equaled 70 percent of their accounting patrimony in 2009. To reduce currency mismatches and to promote dedollarization, Bolivia implemented a prudential policy.

Figure 12 displays the behavior of CM(it) during the event window; the solid and the dashed curves depict the trajectories for Bolivia and for the synthetic unit, respectively. The trajectories are close to each other during the pre-intervention period, indicating the synthetic weights provide a good fit. The reduction of the limit generated a decrease of 0.9 percent in CM(it) over the five quarters after the intervention. More importantly, the policy was effective in reducing long foreign currency positions: the currency mismatch indicator was lower for Bolivia than it was for the synthetic unit in every quarter of the post-intervention period; specifically, CM(it) was on average 2.45 percent lower for

²⁵ This requirement only excludes the policies implemented by Honduras.

²⁶ Also, Guatemala approved the foreign currency positions Act in the first quarter of 2001. This policy is excluded from the control group when is appropriate. However, the policy is not evaluated because there is not a sufficiently large spam of data available in the dataset.

Bolivia. The intervention was also effective in reducing the average currency mismatch: whereas the mean of |CM(it)-1| over the post-intervention period equaled 0.011 for Bolivia, it equaled 0.027 for the synthetic unit.

The Financial Supervisor of Peru (Superintendencia de Banca, Seguros y AFP) also implemented a policy considered in the treatment. The financial supervisor increased the limit on short foreign currency positions. This limit went from 2.5 percent to 5 percent of banks' capital. Figure 13 displays the trajectories of CM(it) associated with the intervention. The trajectories for Peru and for the synthetic unit are similar during the pre-intervention period, signaling again a good fit of the synthetic weights.

Note in Figure 13 that CM(it) did not decrease by a great amount after the intervention: The average rate of decrease over the five quarters equaled to 0.6 percent. However, the comparison with the counterfactual shows the policy was effective in reducing long positions: The value of CM(it) was lower for Peru in every quarter of the post-intervention period. Specifically, CM(it) was on average 8.2 percent smaller for Peru than for the synthetic unit. Along the same lines, the average of |CM(it)-1| over the five quarters after the intervention equaled 0.09 for Peru and 0.18 for the synthetic unit.

Finally, I study the decrease in the limit on long positions implemented by the Central Bank of Paraguay. This limit went from 50 percent to 30 percent of banks' accounting patrimony in October of 2008, with the goals of decreasing currency mismatches and reducing potential maturity mismatches in foreign currency positions.

Figure 14 shows the fit of the synthetic weights is almost perfect during the preintervention period. The CM(it) indicator decreased by 0.29 percent on average over the post- intervention period. This indicator was lower for Paraguay in every quarter after the intervention, with an average difference of 3.92 percent with respect to the synthetic unit. Paraguay also performed better than the counterfactual in terms of average mismatches: whereas the mean of |CM(it)-1| equaled 0.003 for the former, it was equal to 0.042 for the latter.

6.5 Robustness Checks: Average Trajectories

I begin by taking means across all policies in the treatment: That is, I average the trajectories associated with the policies taken by Bolivia (first quarter of 2008 and fourth quarter of 2009); with the intervention implemented by Paraguay (October of 2008) and with the measures carried out by Peru (first quarter of 2004; first quarter of 2005 and first and fourth quarter of 2010).

The solid curve in Figure 15 displays the average trajectory for the treated countries and the dashed curve shows the average trajectory for their synthetic units. Note that, on average, the policies considered in the treatment were effective; the average CM(it) was lower for the treated countries than it was for the synthetic units, with a mean difference of 1.74 percent over the post-intervention period. The policies were also successful in reducing the average currency mismatch: the mean of |CM(it)-1| for the synthetic units was greater than it was for the treated countries (0.46 for the former and 0.28 for the latter).

A concern about the average trajectories displayed in Figure 15 is the inclusion of the four policies implemented by Peru. Peru changed the limit on foreign currency positions twice (the intervention under study plus an additional change) within every of the four event windows. It might then be argued that the difference between the post-intervention trajectories is not driven by the intervention under study (that implemented at the intervention quarter). Therefore, I recalculate the average trajectories displayed in Figure 15, excluding the four policies implemented by Peru.

Figure 16 displays the average trajectories. The policies implemented were on average effective in reducing long foreign currency positions: The average of CM(iT) was lower for the treated countries than it was for the synthetic units in every quarter after the intervention; the mean difference between the averages equaled 2.66 percent over the post-intervention period. The mean of |CM(it)-1| was 0.12 for the treated countries and equaled 0.39 for the synthetic units: The policies also reduced the average level of currency mismatch.²⁷

²⁷Note that the difference between the average trajectories is greater when the policies implemented by Peru are not considered. This outcome is basically explained by the fact that the policy implemented by Peru in the fourth quarter of 2010 did not reduce CM(it).

7. Conclusions

In this paper, I have collected data on assets and liabilities in the banking sector of some Latin America and the Caribbean. These data has allowed me to construct measures of currency mismatch that circumvent issues with existing indicators. In paritcular, I have constructed indicators that are based on sectoral-level information broken down by currency of denomination. I have shown that, when measuring currency mismatch, the data is not replaceable with data based on the residence principle. The residence principle refers to a country's relations vis á vis non-residents but is silent on the currency of denomination.

Employing the novel datset, I have shown the existence of new stylized fact. The trend in foreign currency positions broke after 2007 in several banking sectors. This fact is consitent with a generalized reduction in long foreign currency positions and with the emergence of short position in the second half of the 2000s. I have claimed these facts can be partially explained by the de-dollarization policies implemented in some of the economies in the region. Employing a methodology that has never used to this end, I have evaluated some of these policies in Bolivia, Paraguay and Peru. I have shown that these policies were succesful in reducing long positions and the average level of currency mismatch.

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8. Appendix Section

8.1. Mathematical Approach to Synthetic Control Method

Suppose the outcome variable is observed in J + 1 countries and the policy is implemented at time $t = T_0$ for $t = 1....T...T_0$ by the first country. Let X_1 and X_0 be (*Kx*1) and (*KxJ*) matrices which contain pre-intervention values of *K* predictors of the outcome variable for the treated and for the control countries, respectively, and let *V* be a diagonal matrix that reflects their relative importance. The synthetic method chooses a (*Jx*1) vector of weights

W to minimize $(X_1 - X_0 W)' V(X_1 - X_0 W)$ s.t. $\sum_{j=2}^{j=J+1} w_j = 1$ and $w_j \ge 0$: weights are restricted

to be non-negative and smaller than one to prevent extrapolation outside the support of the outcome variable. The counterfactual is then calculated as $Y^* = Y_0 W^*$, where W^* is the vector of weights that solves the minimization problem and Y_0 contains the values of the outcome variable for the control countries.

8.2. Tables and Graphs

Country	Data Available for:
Argentina	1999Q4-2012Q3
Aruba	1999Q1-2012Q4
Bolivia	2000Q1-2012Q4
Brazil	2001Q1-2012Q4
Chile	1992Q1-2012Q4
Colombia	2000Q1-2012Q3
Costa Rica	1999Q4-2012Q3
Dominican Republic Countries	2000Q4-2012Q4
Eastern Caribbean	1992Q1-2012Q1
Guatemala	2001Q2-2012Q2
Honduras	1998Q1-2012Q4
Jamaica	2000Q1-2012Q4
Mexico	2000Q4 -2012Q3
Nicaragua	2003Q1-2012Q3
Paraguay	1995Q1-2012Q3
Peru	2001Q1-2012Q4
Uruguay	1999Q4 -2012Q4

TABLE 1: DATA COLLECTED IN THE SURVEY

Sources: National authorities.

* The data refers to FX assets and FX liabilities in the banking sector

Country	Proportion of Commercial Banks in Delivered Set
Argentina	99
Aruba	100
Bolivia	100
Brazil	N.A.
Chile	100
Colombia	100
Costa Rica	100
Dominican Republic Countries	N.A.
Eastern Caribbean	100
Guatemala	100
Honduras	100
Jamaica	75
Mexico	N.A.
Nicaragua	100
Paraguay	96
Peru	100
Uruguay	100

TABLE 2: COMMERCIAL BANKS IN DELVERED SET

Sources: National authorities.

* The information cannot be separated into data on commercial banks and data from other financial institutions only in Argentina, Jamaica and Paraguay.

TABLE 3: FX ASSETS/FX LIABILITIES BIS PROXY

DISTNOAT			
Correlation* Coefficient			
0.19			
-0.56			
0.05			
0.66			
0.33			
0.25			
-0.42			
0.74			
0.54			
0.88			
0.19			
-0.82			
-0.06			
0.58			
0.24			

Sources: National authorities, author's calculations and BIS Locational Statistics. * Correlation between FX Assets/FX Liabilities International Claims/International Liabilities ** Period: 2000/Q1-2012/Q3, unless no available data either at my dataset or at BIS statistics.

TABLE 4: FX ASSETS/FX LIABILITIES I.F:S. PROXY

Country	Correlation* Coefficient
Argentina	-0.45
Aruba	0.49
Bolivia	0.10
Brazil	0.83
Chile	0.43
Colombia	0.17
Costa Rica	-0.17
Dominica	0.10
Guatemala	-0.25
Honduras	-0.03
Jamaica	0.74
Mexico	-0.55
Nicaragua	0.40
Paraguay	0.17
Peru	0.68
Uruguay	0.43
NY 1 1	

Sources: National authorities, author's calculations and IFS/IMF.

* Correlation between FX Assets/FX Liabilities Foreign Assets /Foreign Liabilities..

Period: 2000/Q1-2012/Q2, unless no available data either at my dataset or at IFS/IMF

TABLE 5. DEVELOPMENT OF FINANCIAL DERIVATIVES MARKET

(Derivatives Assets + Derivativ Country Liabilities) / (Assets + Liabilitie		Period
Chile	0.0370	2010M1-2013M7
C olombia	0.1217	2000Q1-2012Q3
Nicaragua	0.0007	2008M1-2013M6

Sources: National authorities and author's calculation.

* The ratio of (Derivatives Assets + Derivatives Liabilities is a proxy for the development of derivatives market.

Country	Country CMABS(iT)* Standard Country	CMABS(iT)*	Standard		
Country	CIVIADS(II)	Deviation**	Country	CIVIABS(TT)*	Deviation**
Bolivia	0.0415	0.0200	Brazil	0.1497	0.0857
Paraguay	0.0474	0.0385	Argentina	0.2206	0.0842
Uruguay	0.0520	0.0171	Colombia	0.2824	0.1698
Peru	0.0673	0.0479	Aruba	0.2849	0.1052
Dominican Republic	0.0701	0.0671	Jamaica	0.3270	0.2776
Honduras	0.0800	0.0224	Nicaragua	0.3333	0.2306
Costa Rica	0.1077	0.0380	Eastern Carib. Countries	0.3429	0.2547
Mexico	0.1107	0.0426	Chile	0.3500	0.2862
Guatemala	0.1362	0.0598			

TABLE 6. ABSOLUTE VALUE INDICATOR OF CURRENCY MISMATCH

Sources: National authorities and author's calculations.

* $CMABS(iT) = \left[\sum_{t=0}^{t=T} |CM(it) - 1|\right] / T$ as shown in Equation (1).

** This column refers to the standard deviation of |CM(it)-1|.

*** The sample begins in 2000 and ends in the last available quarter for each country. For the 4 countries with no data available for 2000, I start the sample in first available quarter.

FIGURE 1. ABSOLUTE VALUE INDICATOR OF CURRENCY MISMATCH



Sources: National authorities and author's calculations. **Note 1**: Section 5 provides the formula for the indicators:

|CM(it)-1| = |FxAssets(it) / FxLiabilities(it)-1|

Note 2: The sample begins in 2000 and ends in the last available quarter for each country. For the four countries with no data available for the first the period of 2000, I start the sample in the last available quarter.

Note 3 : The following abbreviations apply: ARG (Argentina); ARU (Aruba); BOL (Bolivia); BRA (Brazil); CHI (Chile); COL (Colombia); CRC (Costa Rica); DOM (Dominican Republic); ECCU (Eastern Caribbean Countries); GUA (Guatemala); HON (Honduras); JAM (Jamaica); MEX (Mexico); NIC (Nicaragua); PAR (Paraguay); PER (Peru) and URU (Uruguay).

Constant	Initial	Change in	Country	Initial	Change in
Country Mean*	Mean*	Means**		Mean*	Means**
Brazil	0.730	3.52%	Argentina	1.143	0.06%
Uruguay	1.046	-0.24%	Guatemala	1.151	-4.49%
Bolivia	1.053	-3.14%	Costa Rica	1.164	-3.74%
Dominican Republic	1.072	-2.83%	Eastern Carib. Countries	1.241	-7.74%
Peru	1.094	-3.52%	Aruba	1.251	4.20%
Honduras	1.100	-0.44%	Colombia	1.347	-8.62%
Paraguay	1.104	-3.37%	Chile	1.606	-33.90%
Mexico	1.119	-1.79%	Jamaica	1.680	-19.89%

TABLE 7. CHANGE IN NON ABSOLUTE VALUE INDICATOR OF CURRENCY MISMATCH

Sources: National authorities and author's calculations

* Initial Mean is the average of CM(it) = FxAssets(it) / FxLiabilities(it) over the period 2001Q2-2002Q1.

**Change in Means: Rate of change between the initial mean and the final mean, which is the average of CM(it) over the period 2001Q2-2002Q1.

Country	CM(iT)*	Country	CM(iT)*
Brazil	0.8523	Mexico	1.1107
Bolivia	1.0337	Guatemala	1.1362
Uruguay	1.0437	Argentina	1.2206
Paraguay	1.0472	Colombia	1.2805
Peru	1.0519	Aruba	1.2849
Dominican Republic	1.0690	Eastern Carib. Countries	1.3037
Honduras	1.0800	Jamaica	1.3270
Chile	1.0934	Nicaragua	1.3333
Costa Rica	1.1077		

TABLE 8. NON ABSOLUTE VALUE INDICATOR OF CURRENCY MISMATCH

Sources: National and authorities and author's calculations.

* $CM(iT) = \sum_{t=0}^{t=T} CM(it) / T = \sum_{t=0}^{t=T} (FxAssets(it) / FxLiabilities(it)) / T$ as shown in Equation (2).

** The sample begins in 2000 or the first available quarter and ends in the last available quarter.

FIGURE 2. NON ABSOLUTE VALUE INDICATOR OF CURRENCY MISMATCH



Sources: National authorities and author's calculations.

Note 1: The rate of change in CM(it) = FxAssets(it) / FxLiabilities(it) is calculated between the initial mean (2001Q2-2002Q1) and the mean of the period that goes from 2011Q3 and 2012Q2. **Note 2** : The following abbreviations apply: ARG (Argentina); ARU (Aruba); BOL (Bolivia); BRA (Brazil); CHI (Chile); COL (Colombia); CRC (Costa Rica); DOM (Dominican Republic); ECCU (Eastern Caribbean Countries); GUA (Guatemala); HON (Honduras); JAM (Jamaica); MEX (Mexico); NIC (Nicaragua); PAR (Paraguay); PER (Peru) and URU (Uruguay).

FIGURE 3. NON ABSOLUTE VALUE INDICATOR OF CURRENCY MISMATCH



Sources: National authorities and author's calculations. Sources: National authorities and author's calculations. Note 1: The Hodrick–Prescott filter yields the trend. Note 2: Monotonic decrease in trend since 2005. Note 3: Minimum value of trend: 2012/Q4.

Note 1: The Hodrick–Prescott filter yields the trend. Note 2: Monotonic decrease in trend since 2002. Note 3: Minimum value of trend: 2012/Q4.



Note 1: The Hodrick–Prescott filter yields the trend. Note 2: Monotonic decrease in trend until 2011/Q3. Note 3: Minimum value of trend: 2011/Q3.

Sources: National authorities and author's calculations. Sources: National authorities and author's calculations. Note 1: The Hodrick–Prescott filter yields the trend. Note 2: Monotonic decrease 1999/Q1-2011/Q2. Note 3: Minimum value of trend: 2011/Q2.

FIGURE 5.



Note 1: The Hodrick–Prescott filter yields the trend. **Note 2:** Monotonic decrease in trend since 2004/Q3. Note 3: Minimum values of trend: 2001 and 2012/Q4. Note 3: Minimum value: 2001-2002 and 2011/Q2.

Sources: National authorities and author's calculations. Sources: National authorities and author's calculations. Note 1: The Hodrick–Prescott filter yields the trend. Note 2: Monotonic decrease in trends since 2007/Q3.



FIGURE 9.

FIGURE 10.

Note 1: The Hodrick–Prescott filter yields the trend. Note 2: Monotonic decrease in trend since 2005/Q3. Note 3: Minimum values of trend: 2012/Q1.

Sources: National authorities and author's calculations. Sources: National authorities and author's calculations. Note 1: The Hodrick–Prescott filter yields the trend. Note 2: Monotonic decrease in trends since 2006/Q1. Note 3: Minimum value of trend: 2012/Q4.



Sources: National authorities and author's calculations. Note 1: The Hodrick–Prescott filter yields the trend. Note 2: Monotonic decrease in trend since 2008/Q1. Note 3: Minimum values of trend: 2001-2003 and 2012/Q4.



Sources: National authorities and author's calculations.

Note 1: The policy reduced CM(it) = FxAssets(it) / FxLiabilities(it) in Bolivia relative to the counterfactual (synthetic).



FIGURE 13. POLICY IN PERU

Sources: National authorities and author's calculations.

Note 1: The policy reduced CM(it) = FxAssets(it) / FxLiabilities(it) in Peru relative to the counterfactual (synthetic).

FIGURE 14. POLICY IN PARAGUAY





Note 1: The policy reduced CM(it) = FxAssets(it) / FxLiabilities(it) in Paraguay relative to the counterfactual (synthetic).



FIGURE 15. AVERAGES FOR POLICIES IN THE TREATMENT

Note 1: On average, the policies reduced CM(it) = FxAssets(it) / FxLiabilities(it) relative to the counterfactual (synthetic).



FIGURE 16. AVERAGES FOR POLICIES, EXCLUDING PERU

Note 1: On average, the policies reduced CM(it) = FxAssets(it) / FxLiabilities(it) relative to the counterfactual (synthetic).

Sources: National authorities and author's calculations.

Sources: National authorities and author's calculations.